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Machine learning techniques for early identification of nitrogen variability in maize

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Abstract.

Real-time plant nitrogen (N) status at field scale is essential to enable the most efficient N fertilizer management system. The objective of this study was to ascertain if mobile fluorescence sensor measurements can accurately quantify variability in maize canopy early in the crop growing season using machine learning (ML) techniques. Multiplex®3, fluorescence sensor (Force-A, France) was used to collect plant N status measurements corresponding to the V6 and V9 maize growth stages. Conventionally, several fluorescence channels and derived indices have been employed as predictors in a multiple linear regression analysis strategy to estimate plant nitrogen. These predictors are often cross-correlated among each other, which makes the regression analysis challenging. Hence, the new generation of experiments often leans towards ML strategies. In this current study, fluorescence indices measured at V6 and V9 stages of maize were utilized for recommendations of selecting machine learning strategies among: (1) Partial least-square regression (PLSR), (2) Support Vector Regression (SVR), (3) Gaussian Process Regression (GPR), (4) Random Forest Regression (RFR), and (5) Artificial Neural Network (ANN) Multi-layer perceptron. The preliminary results indicated that ML techniques outperform traditional workflow. The comparative analysis indicated a promising accuracy in estimation of plant N content, above-ground biomass, and N uptake at V6 stages of maize with the moderate range of correlation coefficient ($r = 0.72 \pm 0.03$) and Root Mean Square Error (RMSE). Indeed, the V9 stage results in better retrieval accuracies than V6. Among ML techniques, the Support Vector Regression (SVR) performed best over the test site with a reasonable ranges of error estimates and yielding the lowest RMSE (0.36 and 0.23 (%N); 3.82 and 12.37g (biomass); 8.29 and 32.63g (N uptake) for V6 and V9, respectively) for all three crop growth indicators.

Keywords.
fluorescence; precision agriculture; nitrogen management; machine learning; vegetation indices.

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Introduction

In-season assessment of crop nitrogen (N) status is the prerequisite for optimizing crop N fertilizer management. Instead of destructive plant sampling, indirect methods with the help of remote or proximal sensors have been developed to assess N status (Lemaire et al., 2008). Among these sensors, chlorophyll fluorescence sensing has shown a strong relationship with plant N status (Tremblay et al., 2012). Two N-sensitive indicator compounds are chlorophyll and flavonols. The leaf chlorophyll content is strongly influenced by leaf N (Schepers et al., 1996). In recent years, proximal sensors (e.g., Dualex, Multiplex) were used to identify nitrogen variability in crops (Cerovic et al., 2012; Dong et al., 2020; Siqueira et al., 2020).

In most studies, a correlation between fluorescence measurement and the N status indicator was established, and subsequent parametric regression allowed prediction of plant N (Yang et al., 2016). From a practical perspective, developing such regression models has the advantage that it facilitates the use of fluorescence measurements as an indirect estimation of crop N status indicators at different crop growth stages. Nevertheless, these fluorescence measurements (predictors in the regression analysis) are often cross-correlated among each other, which makes the regression analysis challenging. In recent years, multivariate regression algorithms have been widely applied in the quantitative estimation of the bio-geophysical parameter from remote and proximal sensing using machine learning (ML) strategies (Verrelst et al., 2015; Mandal et al., 2019; Berger et al., 2020).

Considering the complexity of multi-channel fluorescence measurements taken at canopy scale with motion, the ML based regression algorithms can extract major characteristic and can be used to analyze the intricate and complex correlation between fluorescence measurements and crop N indicators (Chlingaryan et al., 2018; Dong et al., 2021). Among several ML models, partial least square regression (PLSR), stepwise multiple linear regression (SMLR), support vector regression (SVR), artificial neural network (ANN) are often used to estimate crop N concentration. In this study, Multiplex®3, fluorescence sensor was used to collect plant N status measurements corresponding to the V6 and V9 maize growth stages. The objective of this study was to ascertain if mobile fluorescence sensor measurements can accurately quantify variability in maize canopy early in the crop growing season using machine learning (ML) techniques.

Materials and Methods

Test site and agricultural management

The present experiment was performed over a test site located at Agricultural Research Development and Education Center (ARDEC) of Colorado State University, Colorado, USA (40°39'57.4"N, 104°59'53.1"W). This site will be referred to as ARDEC in the following sections. The experiment at this site was performed over 2012 crop growing season within a field under pivot irrigation system and maize cultivation. Different N rate treatments were applied in a completely randomized design. UAN 32% (urea and ammonium nitrate; 32-0-0) was applied as nitrogen sources at rates of 0, 56, 112, 168, and 224 kg ha-1. Each of these 5 treatments were laid out according to three management zone (high, medium, and low), with each plot had 6 rows (4.57 m wide and 6 m long). For each N treatment and management zone, 4 repetitions were considered. The plant sampling was conducted at V6 and V9 growth stages of maize. It included determination of above-ground biomass and plant N through destructive sampling. The harvested plant components were sent to laboratory for the analysis of total plant N content (%) and N uptake (g).

Fluorescence data acquisition

The Multiplex®3 (FORCE-A) was used in the present study to acquire fluorescence response from maize canopy. Multiplex®3 has induction light emitting diodes (LED) at four different emission channels (UV-A: 375nm, blue: 470nm, green: 516nm, red: 625 nm). The induce plant fluorescence is detected by three photodiodes (yellow (YF), red (RF) and far-red (FRF)). The fluorescence measurements were carried out with the hand-held Multiplex®3 at the V6 and V9 growth stages of maize. The fluorescence measurements were collected in motion at 10 cm above the plant canopy (Fig. 1). From each plot, ten plants were selected along the third row (center row) for fluorescence data acquisitions. A filtering was performed over fluorescence data acquired on the canopy to compensate noises using wavelet transformation based denoising. These data filtering steps were performed using Python libraries (Code availability: Github[1]).

Fig. 1. Mobile acquisition mode of Multiplex®3 fluorescence sensor over maize canopy in field.

Instead of individual fluorescence channel, several vegetation indices were used. In total, seven indices were selected for this research: Four N balance indices (NBI_R, NBI_B, NBI_B and NBI1), two chlorophyll indices (CHL and CHL1) and one flavonoid index (FLAV) (Agati et al., 2013; Longchamps and Khosla, 2014). The sensitivity of each vegetation indices to different N application rate was subjected to analysis of variance (ANOVA) (significance level $\alpha = 0.01$, and 0.05) at V6 and V9 growth stages of maize. In the case of significant difference, a Tukey's HSD test was used to compare mean values of individual vegetation indices across N treatments at the $p < 0.05$ significance level.

Estimation of crop growth indicators

The fluorescence-based vegetation indices were used as predictors for estimation of crop N indicators, i.e., aboveground biomass, N content (%), and N uptake with the machine learning regression technique. Multivariate predictors were used in ML algorithms during the training phase for each target parameter. The comparison of these ML regression techniques i.e., PLSR, Random Forest (RFR), SVR, ANN, Gaussian Process Regression (GPR), were conducted to elucidate their capabilities under the same agronomic condition and acquisition modes of fluorescence sensor. For comparison of different machine learning techniques in estimation of crop growth indicators, the repeated K fold cross validation score were used (Fig. 2). The test accuracies of ML techniques were compared for %N, biomass, and N uptake at the V6 and V9 growth stages independently.

[1] Codes: https://github.com/PrecisionAgLab-KSU/ICPA2022_Abstract8761

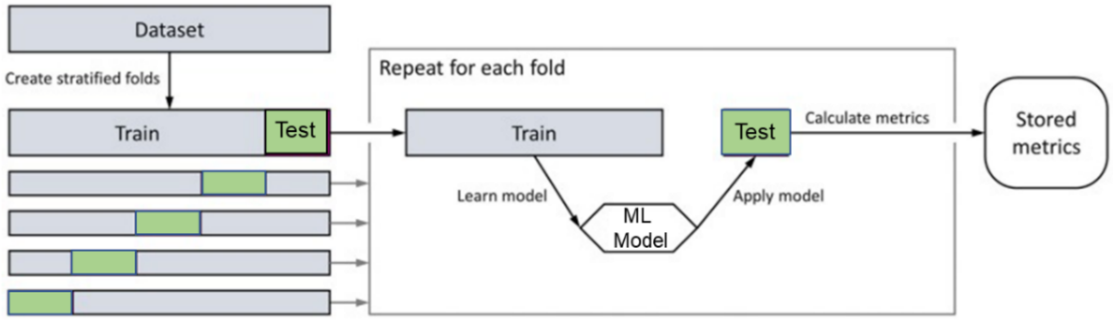

Fig. 2. Schematic workflow for ML model training and validation.

Results and discussions

Sensitivity of fluorescence measurements with different N rate application

The sensitivity of fluorescence indices is presented with different N application rates over experimental plots of the ARDEC site in Fig. 3 and 4 for V6 and V9 growth stages of maize. For statistical analysis, the treatments were split based on three management zones (low, medium, and high).

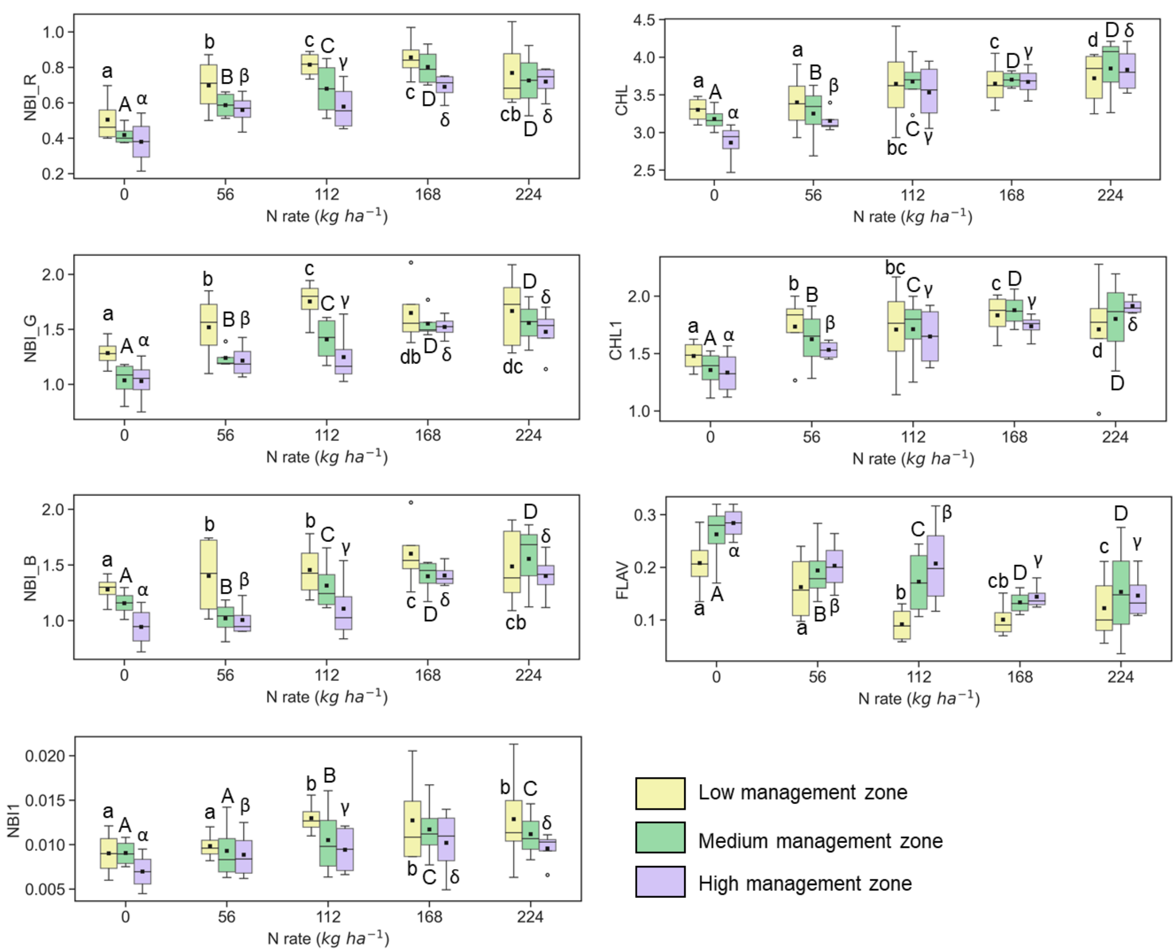

Fig. 3. Response of fluorescence indices to different N application rate at V6 growth stage of maize. Responses are grouped according to the three manazement zones (i.e., low, medium, and high). Different letters (a, b, c, d: Low MZ; A, B, C, D: Medium MZ; α, β, γ, δ: High MZ) indicate significant differences according to the Tukey's HSD test at $p < 0.05$ significance level.

Irrespective of management zones, the NBI measured from red and green induction (NBI_R and NBI_G) showed better distinction among the N treatments (significantly different with α = 0.05) at the V6 stage. The other two N balance indices (NBI_B, and NBI1) indicated lower differences in mean values along with different N treatments.

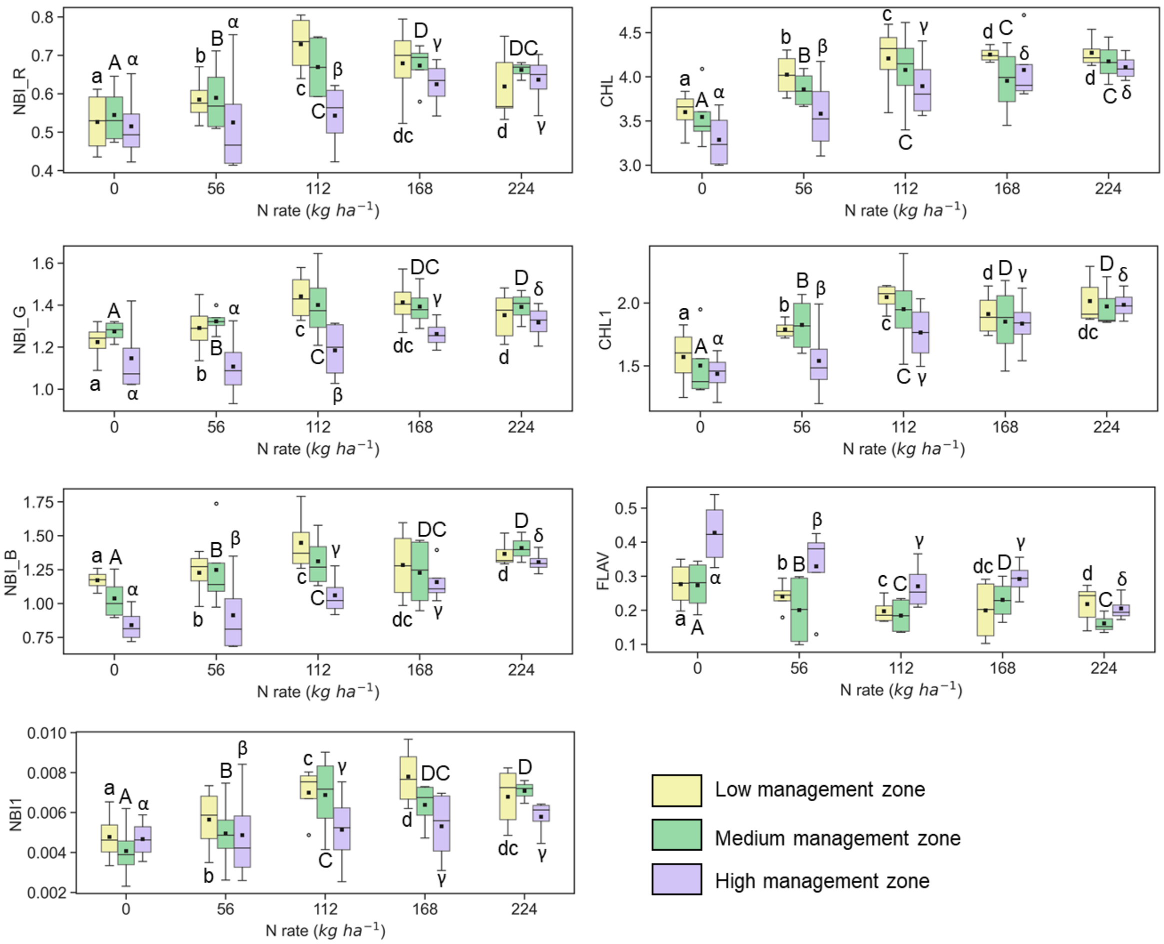

Fig. 4. Response of fluorescence indices to different N application rate at V9 growth stage of maize. Responses are grouped according to the three manazement zones (i.e., low, medium, and high). Different letters (a, b, c, d: Low MZ; A, B, C, D: Medium MZ; α, β, γ, δ: High MZ) indicate significant differences according to the Tukey's HSD test at p < 0.05 significance level.

According to the ANOVA results of fluorescence indices, the effect of N treatment on most of the indices was significant. The NBI_R, NBI_G, NBI_B, NBI1, CHL, and CHL1 increased with the increase of applied N, while decreasing trends were found for FLAV (Fig. 3). However, all the tested fluorescence indices were not sensitive to N rates ranging from 168 to 224 kg ha^{-1} N at the V6 growth stage. Interestingly, these indices were unsuccessful to distinguish the high N rates (>=112 kg ha^{-1}) during the V9 growth stage (Fig. 3). Compared to all indices, FLAV changed inversely with the N rate irrespective of growth stages and management zones. It is possibly due to polyphenols accumulation in leaf epidermis under low N availability, which was opposite to the increasing trend of CHL and CHL1 related to chlorophyll content (Liu et al., 2010).

Comparison of machine learning techniques

For comparison of different machine learning techniques in estimation of crop growth indicators, the repeated k-fold cross validation score was used. The test accuracies for five state of the art machine learning techniques were compared for %N, biomass, and N uptake at V6 and V9 growth stages independently. The error estimates in terms of r and RMSE are presented in Table 1.

Table 1. Test accuracies of maize N status indicator (%N, biomass (g), N uptake (g)) estimation using fluorescence indices at V6 and V9 stages of maize for different machine learning models.

Crop parameter	Model	V6		V9	
		r	RMSE	r	RMSE
%N	PLSR	0.7	0.65	0.68	0.46
	SVR	0.81	0.36	0.83	0.23
	GPR	0.79	0.4	0.82	0.28
	RFR	0.75	0.54	0.76	0.35
	ANN	0.78	0.46	0.8	0.26
Biomass	PLSR	0.73	4.98	0.75	16.58
	SVR	0.83	3.82	0.91	12.37
	GPR	0.84	3.96	0.86	12.98
	RFR	0.79	4.09	0.83	13.68
	ANN	0.8	4.01	0.85	12.87
N uptake	PLSR	0.62	12.05	0.75	40.57
	SVR	0.79	8.29	0.92	32.63
	GPR	0.76	9.06	0.86	33.89
	RFR	0.68	9.85	0.8	36.52
	ANN	0.75	9.02	0.87	33.02

Except the PLSR, marginal differences among other techniques for all three plant N indicator were observed. In the case of %N, the lowest r and higher RMSE values for both the V6 (r = 0.7, RMSE = 0.65) and V9 (r = 0.68, RMSE = 0.46) growth stages were observed for PLSR. The lowest accuracies were obtained for biomass and N uptake. As compared to the machine learning models, PLSR could not handle the multicollinearity between predictors, which affected the training process.

Amongst the other four techniques, the highest accuracy was obtained with the SVR, also yielding the lowest RMSE (0.36 and 0.23 (%N); 3.82 and 12.37 (biomass); 8.29 and 32.63 (N uptake) for V6 and V9, respectively) for all three crop growth parameters within desirable limits. These results supported the conclusion that the SVR is an efficient and robust technique for fluorescence-based crop growth parameter estimation. The performances were inferior at the V6 growth stage. Dong et al. (2020) also reported higher variations in plant nitrogen content estimates at V6 than at V8 stages of maize using fluorescence indices (NBI, FLAV, and CHL).

Summary

Applications of mobile fluorescence sensing for maize under field conditions has proven to be a promising sensing technology for monitoring crop growth. The results of Multiplex fluorescence indices measured over maize canopy treated with different N rates indicated that fluorescence measurements were able to discriminate variances between N rates both at V6 and V9 stages in all management zones. Mobile crop sensors have the potential to provide a real-time estimate of crop N status indicators. While evaluating ML techniques, the cross-validation scores indicated high correlation coefficients and low estimation errors for SVR at V6 and V9 growth stages. These results support a conclusion that the SVR could be an efficient and robust technique for fluorescence-based estimates of crop N status indicators. Nonetheless, a comparison among ML models is necessary on the basis of the time-memory complexity which indicates their robustness, uncertainty, and computation costs for retrieving crop N indicators.

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